Article

Monetary Policy, Portfolio Heterogeneity, and the College Wealth Gap

Alessandro Guarnieri[1]

[1] Student (BSc Economics, 2019-22), Dept. of Economics, UCL, UK; alessandro.guarnieri.19@ucl.ac.uk

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Abstract
This paper investigates the relationship between monetary policy and wealth inequality by college education. I first highlight the extent to which college education drives salient differences in the portfolio composition of U.S. households, and then study how this, in turn, affects households' exposure to asset price changes following an expansionary monetary shock. This paper contributes to an evolving body of literature exploring the role of portfolio choices and, in particular, stock market participation, on the distribution of capital gains following policy shocks. I show that accommodative monetary policy substantially exacerbates the existing wealth gap between college-educated households and households without a college degree. Monetary policy is thus limited, as it cannot stimulate economic activity without widening wealth inequality.

Keywords: Monetary Policy, Wealth Inequality, Education, Portfolio Effects

1. Introduction

Inequalities caused by education have traditionally been outside the purview of monetary authorities. However, an evolving strand of literature has explored the role played by household heterogeneity in the transmission mechanisms of macroeconomic policies. In this paper, I investigate the correlation between monetary expansion and wealth inequality by college education. At the heart of this study is the idea that expansionary monetary policy may exacerbate existing disparities in wealth due to its effect on the valuation of housing and equity. As my analysis shows, college education is indeed strongly correlated with salient differences in household portfolio composition, thus driving heterogenous exposure to capital gains following monetary shocks.

Most of the existing academic literature on monetary policy and inequality has focused on the so called 'earnings channel' (see Coibion et al. (2017)); by stimulating economic activity, monetary easing particularly benefits individuals who would otherwise be unemployed. Since workers who are drawn into the labour market are predominantly low-skilled and from low-income households, inequality as measured by earned income and employment gaps is reduced. On the other hand, an investigation of the 'portfolio channel' of monetary policy and its distributional implications is still very much in its infancy. Moreover, while a growing number of papers have highlighted the role played by heterogeneity in household portfolios (e.g., Kaplan et al. (2018) and Cloyne et al. (2020)), an effort to identify structural drivers of such balance sheet differences is almost entirely absent from the existing literature.

In order to measure the effect of monetary shocks on the college wealth gap, I first rely on survey data on US households from an extended version of the Survey of Consumer Finances (SCF+). Using this data, I measure the extent to which college education is correlated with not only the size, but also the composition of families' portfolios. As I shall explain in greater detail, there is compelling evidence that whether or not households hold a college degree and their exposure to stock- and house-market booms are strongly related. Importantly, this correlation remains strong when households with the same income are compared. I then move on to study the movements of asset prices following an expansionary monetary policy shock. To that end, I estimate local projections over a horizon of 48 months using the Romer and Romer (2004) monetary shock series for identification of exogenous changes in the federal funds rate. Point estimates from this analysis show substantial and temporary increases in stock prices (up over 8% at their peak), and more modest but significant and persistent increases in house prices (peaking at just short of 4%) following a 100bp expansionary monetary policy shock.

By combining the point estimates from the local projections with evidence from the SCF dataset, I show that monetary easing leads to substantially larger wealth gains for households with a college degree. Indeed, the average household with a college degree gains over five times as much as the average household without college education. Substantial inequalities persist if households within the same income group are compared. Interestingly, when gains are computed as a percentage change in wealth rather than as the dollars-denominated difference in average wealth, benefits appear more equally distributed. Nevertheless, I argue that absolute capital gains matter more for inequality than per cent ones given the initial level of concentration of wealth.

As the following section highlights, this paper might be thought of as building on the work of Bartscher et al. (2021), who find that expansionary monetary policy increases racial inequality between black and white households in the United States due to its price effects. By focusing on a different driver of balance sheet heterogeneity, i.e. college education, I bring greater generality to the distributional implications of monetary shocks. Moreover, evidence from the UK and US shows that inequalities in educational attainment are particularly persistent at higher (e.g. university) qualifications (see Blanden and Mcmillian (2016) for the UK and Chetty et al. (2020) for the US). Hence, the paper's focus on college education is relevant as it identifies a redistribution channel of monetary policy likely to persist despite the general expansion in educational level. Hence, along with evolving evidence from the academic literature, this paper highlights practical limitations of monetary policy, and it warrants broader policy mixes.

Structure of this paper: Section 2 provides a discussion centred on the existing literature on monetary policy and inequality. In Section 3, I first describe the survey data available through the SCF, and then show how college education increases exposure to asset price changes. The instrumental variable local projections (LP-IV) approach which I implement to obtain impulse responses is presented in section 4. The distributional effects of the monetary

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shock are computed in Section 5, where I combine the micro data with point estimates from the LP-IV model. Section 6 concludes.

2. Literature Review

2.1. The Distributional Impact of Monetary Policy: Evidence from the Literature

2.1.1. The Earnings Channel

Academic literature on the distributional effects of monetary policy is still in its infancy, with most of the previous research focusing on income rather than wealth. Since poorer households are generally worse hit in a recession, expansionary monetary policy decreases income inequality by stimulating employment. Coibion et al. (2017) refer to this effect as the 'earnings channel'. Their work, based on survey data of US households, suggests that higher interest rates have significant adverse effects on labour earnings and consumption inequality. Similar findings are reported by Mumtaz and Theophilopoulou (2017) for the UK, and by Furceri et al. (2017) - based on a study of 32 advanced and emerging economies. Samarina and Nguyen (2019) point to the same channel when measuring the effect of expansionary monetary policy shocks in the Eurozone.

2.1.2. The Portfolio Channel

A growing number of papers investigates a second channel which operates through the effect of easier monetary policy on asset prices. Given the concentration of asset holdings among households, this channel increases inequality as measured by wealth and capital income. Kaplan et al. (2018) explore the transmission mechanisms from conventional monetary policy to household consumption in a Heterogeneous Agent New Keynesian (HANK) model. The model's results show that elasticity of consumption is higher for households with sizable ownership of illiquid assets, equity being the most important. The primary role of equity and housing holdings is also highlighted in Domanski et al. (2016) and Cloyne et al. (2020); the latter conclude that households owing mortgage debt (and hence the lot of middle-income households) are the most responsive to decreases in interest rates. This group is characterized by little or no liquid wealth and sizable illiquid wealth, thus displaying hand-to-mouth behaviour, i.e. high marginal propensity to consume out of small changes in their income. It is worth noting that the consumption response to monetary policy does not necessarily reflect higher wealth gains for middle-income households relative to others. Indeed, Albert and Gòmez-Fernàndez (2018) focus on the wealth-effect of expansionary monetary policy, showing simulations that predict that the poorest and wealthiest benefit the most when monetary policy is loose. Ongoing work by Melcangi and Sterk (2020) for the Federal Reserve Bank finds that the stock market channel of monetary policy quantitatively dominates the consumption channels often emphasized in the literature. In the same vein of research, Holm et al. (2021) use HANK models to investigate the role played by household liquid asset positions on the direct and indirect effect of monetary policy in Norway. The authors show that wealth inequality decreases in response to a monetary tightening, an effect driven primarily by capital losses accruing from risky financial assets. Andersen et al. (2021) investigate the wealth of Danish households using administrative data, and find a monotonic relationship whereby lower interest rates increase wealth and total income more the wealthier is the household to begin with. The general consensus in these papers is that household heterogeneity is key in order to pin down the true distributional implications of monetary shocks.

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2.2 Drivers of Wealth Composition: Education and Portfolio Choices

To the best of my knowledge, very few researchers have narrowed their focus to a particular driver of differentials in households' portfolio composition. Bartscher et al. (2021) explore the role of race by studying the effect of expansionary monetary policy on earnings and wealth differentials between White and Black households in the United States. The authors show that the portfolio shares of housing, equities and bonds, are significantly larger for White households, thus exposing their wealth to changing asset prices much more than for Black households. Overall, a small reduction in the earnings gap is dwarfed by the increase in the wealth gap, implying that expansionary monetary policy has a significant adverse effect on racial inequality. Clearly, a similar argument holds for different drivers of balance sheet heterogeneity (i.e. other than race). Previous research on educational differences conducted by Bartscher et al. (2019) has documented significant heterogeneity in terms of financial developments, giving rise to different exposures to asset price changes. Lusardi et al. (2013) construct a stochastic lifecycle model characterised by endogenous financial knowledge accumulation. The simulations show that financial literacy can explain a large fraction of the observed wealth inequality.

3. College Education and Wealth Composition: Evidence from Survey Data

In this section, I provide a description of the household survey data which inform the first empirical analysis of this paper. I use information on families' financial positions and savings decisions to uncover the extent to which households with different educational levels in the United States make different portfolio choices.

3.1. Survey Data: The Extended SCF Dataset

The first part of this research makes use of survey data from an extended version of the Survey of Consumer Finances. The SCF is (normally) a triennial cross-sectional survey of US households. It contains rich information on families' financial position, including balance sheet composition, pensions, income, and relevant demographics. An important feature of the survey is that it over-samples wealthy households; all of the results shown in the paper are re-weighted following Kuhn et al. (2018) to avoid biased estimates.[1]

The SCF was extended by Kuhn et al. (2018) based on historical surveys conducted at an annual frequency from 1947 to 1971, and again in 1971, by the Survey Research Centre of the University of Michigan. Table 1 shows how I combined such financial information available with the SCF+ to construct variables of household holdings of all asset classes. I do so consistently with Bartscher et al. (2021) (see footnote 6 in their paper), who in turn use the approach of Bricker et al. (2017)

Final variable	Composition using SCF+ dataset
Bonds	Bonds + Saving bonds
Housing	Asset value of house + Other real estate
Stocks	Equity and other managed assets + business wealth + mutual funds
Liquidity	Liquid assets + Certificates of deposits
Other financial	Other financial assets + Life insurance assets + Pensions
Other non-financial	Other non-financial assets + Vehicles

Table 1: Computation of Household's Wealth Holdings by Asset Type

NOTE: Variables in the right column are already available with the version of the SCF+ which was kindly provided by Moritz Kuhn and Alina Bartscher (see footnote). Variables on the left were generated following the approach in Bartscher et al. (2021)

[1] The SCF+ was kindly provided by Moritz Kuhn and Alina Bartscher (Bonn University). The formatted dataset includes the 'weight' variable used to account for oversampling of wealthy households.

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In this extended version of the SCF, data is available from 1947 to 2019. However, distinction between households with a college degree and without is only available in waves of the survey from 1956 onwards. Hence, all of the results shown in the following sections are obtained by truncating the sample (i.e. dropping observations from before 1956).

As mentioned in the introduction, the survey data is used to estimate how much obtaining a college degree correlates with household exposure to asset price changes (see Section 3.2). Since data is at the household- rather than individual-level, I divide households into 'college' or 'non-college' groups depending on whether the household head holds at least a bachelor's degree. Householders with 'some college education' are included in the group of non-college households. This approach is consistent with Bartscher et al. (2019) and reflects notable portfolio differences between households with some college versus a college degree. It should also be noted that the dataset contains multiple imputed observations which are averaged for the regressions.

3.2. Results; Asset Price Exposure by College Education

As anticipated in Section 3.1, the extended SCF dataset allows the study of the relationship between households' level of education and their saving decisions. What is more relevant to this paper, it allows us to measure how, on average, households with and without a college degree diversify their wealth across different asset classes.

Before looking at this, it is worth investigating the more general effect of college education on wealth, and hence observe how the 'college wealth premium' has evolved over time. Fig. 1 recreates and extends results from Bartscher et al. (2019) by showing the trend in wealth from 1956 to 2019 for households with and without a college degree. Fig. 1(A) clearly displays the widening of the college wealth gap starting from the 1980s. When individuals within the same wealth group are compared (Fig. 1(B)), the positive college wealth premium remains evident for households in the top 50 percent of the wealth distribution. These figures display unconditional averages, meaning that they do not show what role demographics and other characteristics play for the observed wealth gap.

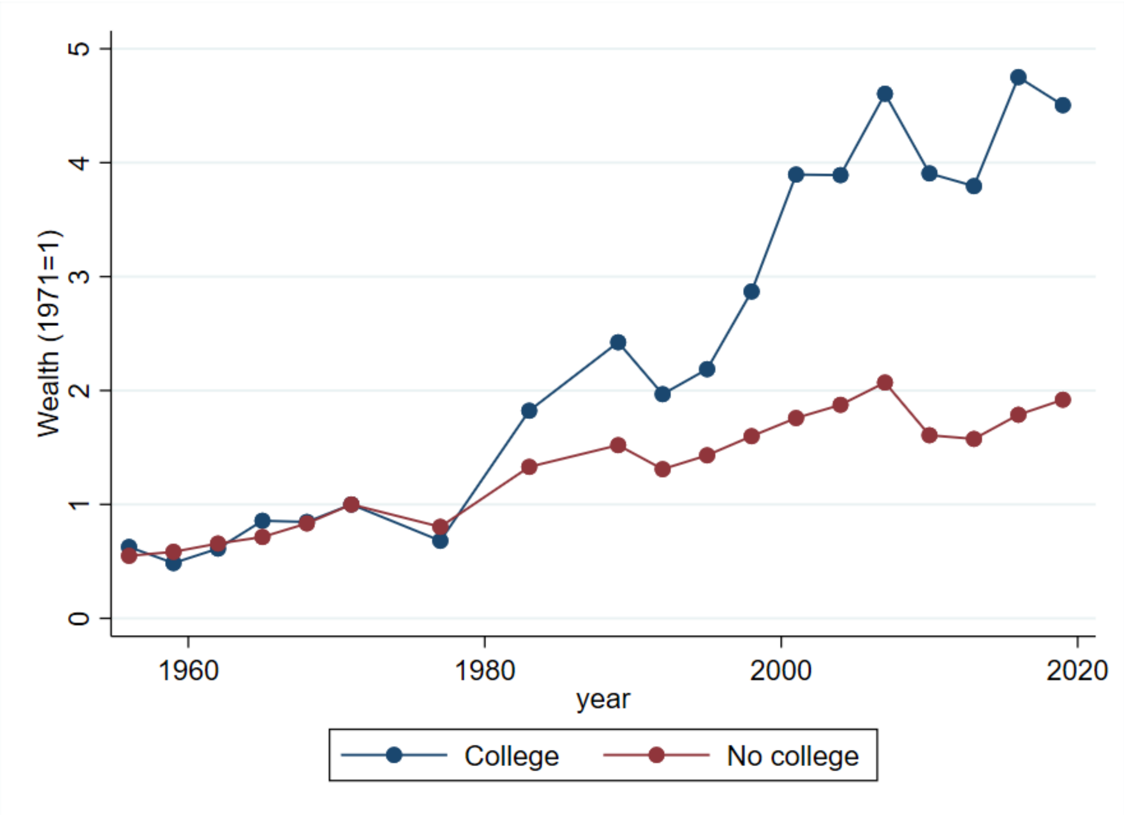

Figure 1(A)

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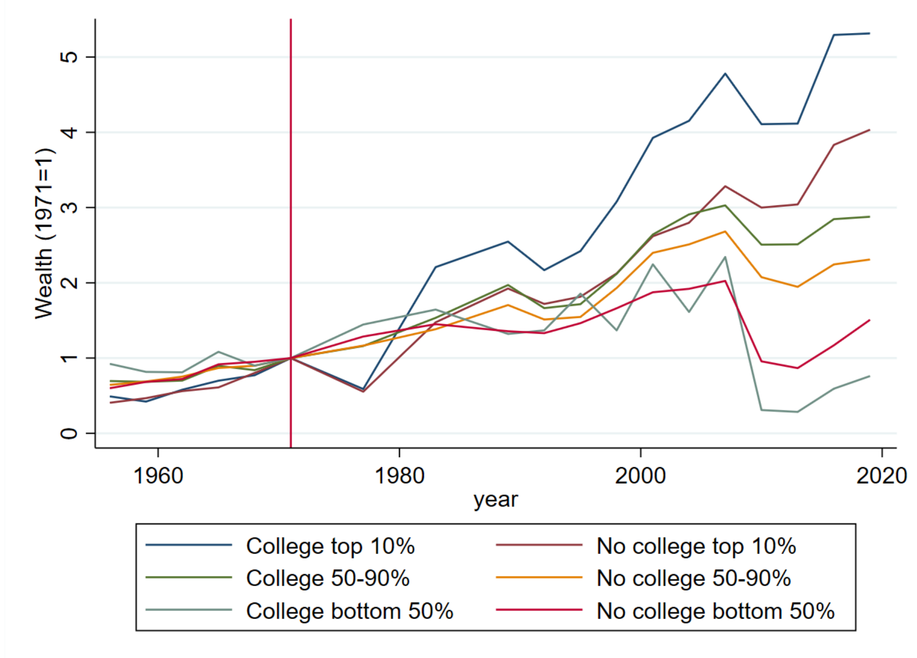

Figure 1(B)

Further extending results from Bartscher et al. (2019), I estimate regression equation 3.2.1.

$$W_{it} = \beta_0 + \beta_1 c_{it} + \sum_{t\geq 1956}^{2019} \beta_{2,t} \mathbb{1}_{[year=t]} \cdot c_{it} + \sum_{t\geq 1956}^{2019} \beta_{3,t} \mathbb{1}_{[year=t]} + \gamma' X_{it} + \epsilon_{it}. \qquad (3.2.1)$$

where c_{it} is a binary variable equal to 1 if household i holds a college degree and 0 otherwise. 1[year=t] is an indicator function to capture survey wave fixed effects for t = {1956, 1959, ..., 2019}. I also add a vector of controls X including a full set of age dummies, number of children in the family, marital status, race, and, importantly, family's total income. Fig. 2 shows the time trend of the estimated parameters $\widehat{\beta}_1 + \hat{\beta}_{2,t}$.

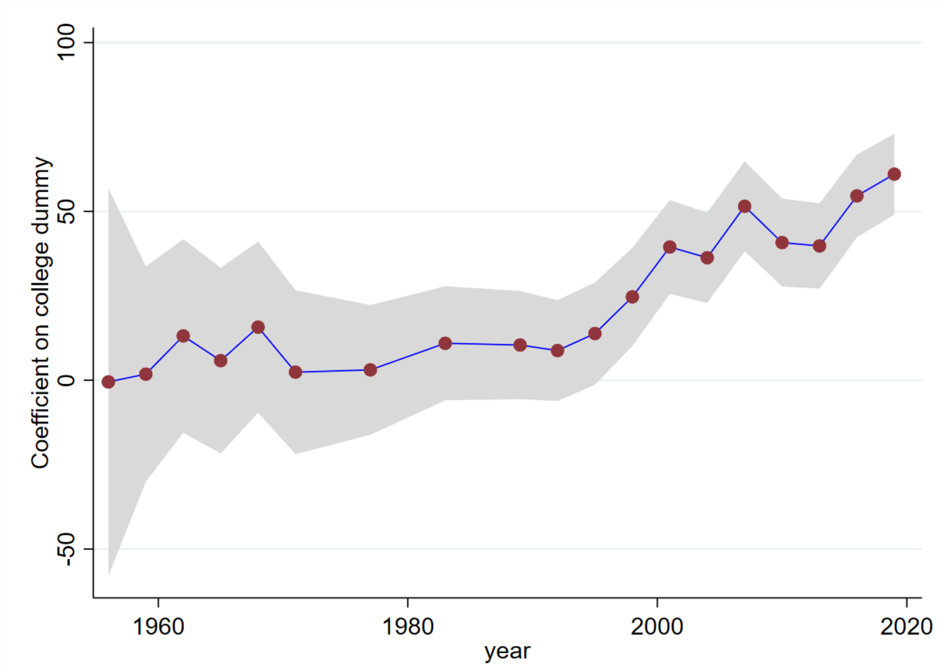

Figure 2

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This shows that, even after controlling for total income, the increase in the college wealth premium over time is strong. Everything else being equal, in 2019 holding a college degree is estimated to increase household wealth by over $60,000 US dollars. Appendix A.2 provides numerical results of the regression model above.

Having shown the general trend in wealth inequality between college- and non-college educated families, I now turn to analysing whether a relationship exists between education and the composition of household balance sheets. To do so, I construct variables of asset classes as shown in Table 1, and compute the wealth share of each asset. This allows us to obtain a first sense of salient differences in asset price exposure. Results are shown in Fig. 3. This is readapted from Figure 12 in Bartscher et al. (2019) to fit the asset classes composition shown in Table 1. It is worth noting that the results shown in this section are consistent with their main findings, i.e. that there are substantial differences in the portfolio composition of US families based on their level of education; in particular, that stocks, bonds, and other financial assets take up a much larger share in families' balance sheets if the household head holds a college degree, while the opposite is true for housing and non-financial assets. In addition, representativeness in the SCF+ dataset allows us to make the claim that such differences are not just a consequence of sampling variation.

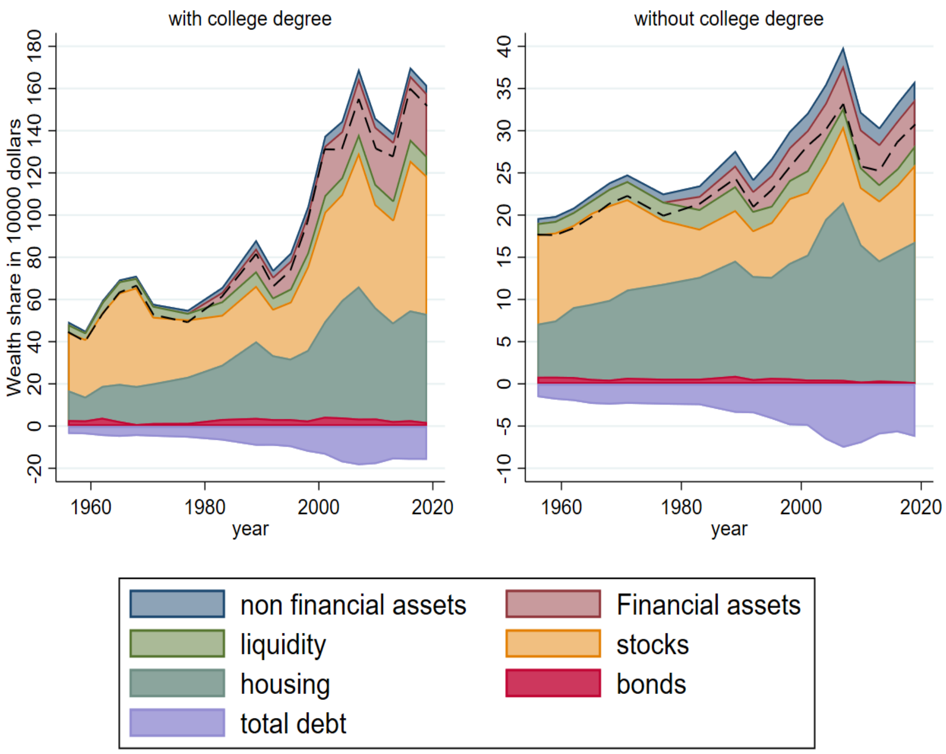

Figure 3

NOTE: The black dashed line in the panels shows total real net wealth. Indeed, we can notice that the sum of all assets minus debt almost exactly matches the black dashed line (net wealth) in both panels.

The figure shows the evolution in the composition of wealth by 'asset class' for households with a college degree (left panel) and without college degree (right panel). The most notable findings are:

1. Households with a college degree are significantly more exposed to changes in the valuation of stocks and other financial assets compared to less educated families.
2. Non-college households are, at least as a percentage of total wealth, more exposed to changes in house prices.

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This is consistent with results by Domanski et al. (2016), who find that changes in house and equity prices tend to have opposite effects on wealth inequality. Fig. 4 shows the wealth share of each asset class in 2019:

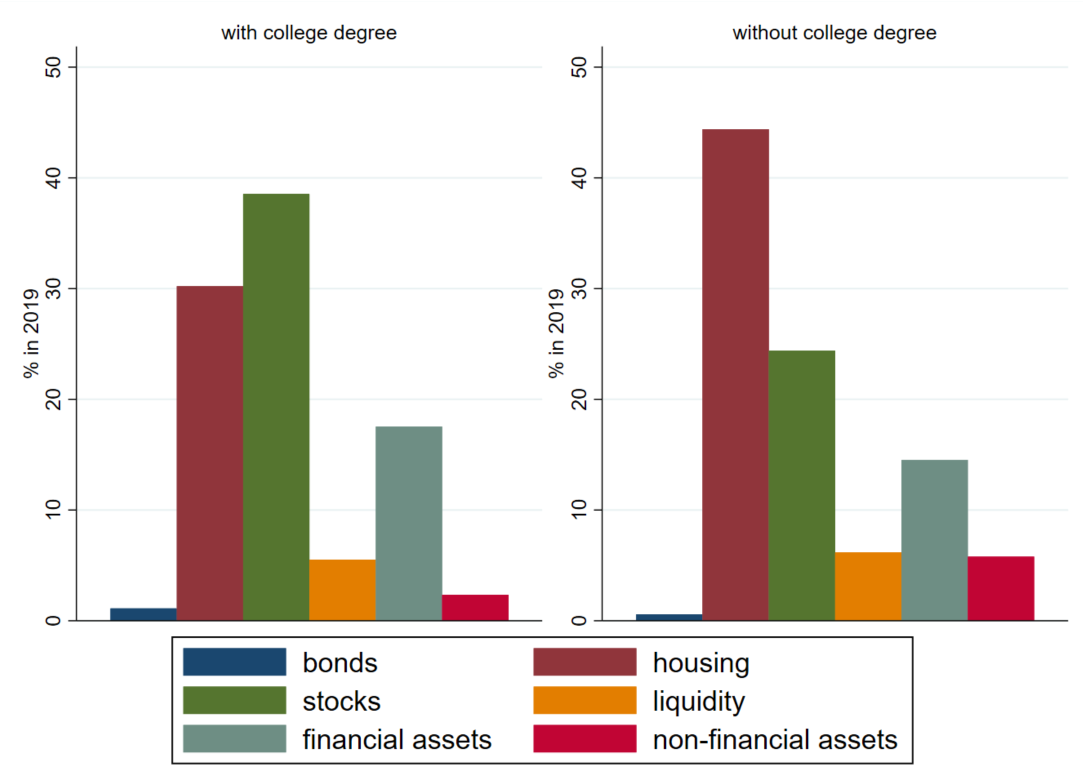

Figure 4

College-educated households save 38.56% of their wealth in stocks, and 30.22% in houses and other real estate. On the other hand, non-college households save, on average, 44.39% of their wealth in housing and 24.39% in stocks. In both groups, housing and stocks account for just short of 70% of their total wealth. Hence, movements in equity and house prices have significant portfolio effects for US households. It should be noted that this paper does not claim to measure the *causal* effect of college education on either the size or composition of families' balance sheets. For example, unobserved family traits unrelated to income might contemporaneously affect households' saving decisions as well as their attitudes towards university education; an example of such traits might be risk aversion. Nevertheless, by documenting a strong relationship in the data between educational level and portfolio choices, this work adds to an active research agenda questioning the neutrality of monetary policy.

Following Bartscher et al. (2021), I multiply a 10% increase in asset prices with the average stock of asset holdings of the respective educational group. So far I have not accounted for differences in income among households. When computing measures of asset price exposure, I distinguish between households based on their income group. In particular, the SCF+ allows us to compare capital gains for households in the bottom 50% of the income distribution, in between the 50 and 90%, and in the top 10%. The purpose of such differentiation is twofold: firstly, it investigates whether differences in asset price exposure between college and non-college households remain significant even when households belong to the same income group; secondly, it provides interesting insights into the interaction of education and income in shaping households' saving decisions. The results of this analysis are shown in Fig. 5 as well as Table 2.

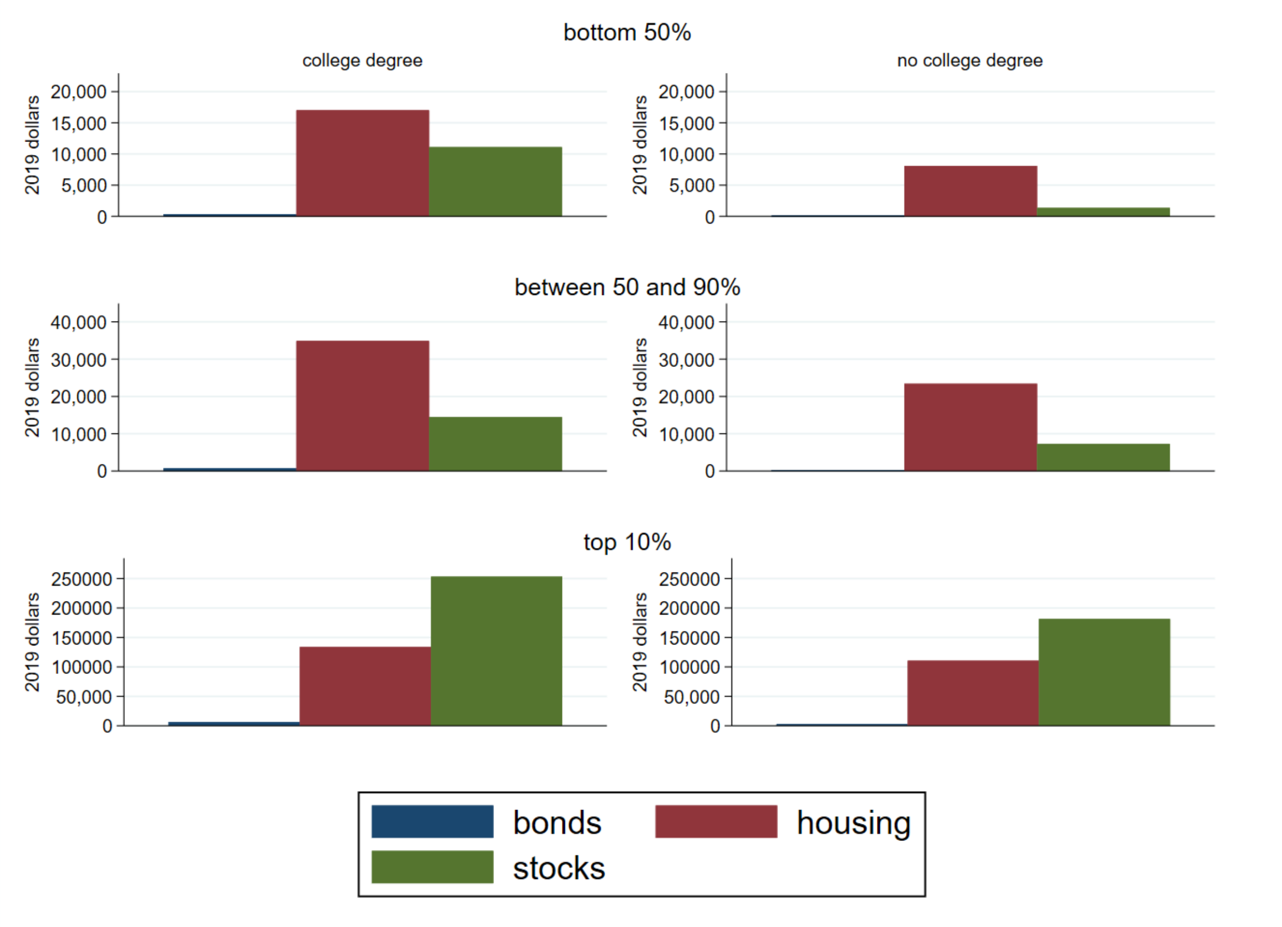

Figure 5

As shown in the figure, college education in the SCF+ remains positively correlated with exposure to asset price changes even when college and non-college households are in the same group within the income distribution; this is true across all income groups and asset classes. An interesting finding is that housing actually constitutes the main asset for both college and non-college households apart from the top 10%, which saves most of its wealth in equity. Therefore, the equity share of wealth in excess of housing shown for college households in Fig. 4 is driven entirely by the top 10%. This is consistent with findings by Kuhn et al. (2018), who uncover that stocks are an asset class primarily held by the top 10%.

Asset type	College Degree			No college degree		
	Bottom 50%	Between 50% and 90%	Top 10%	Bottom 50%	Between 50 and 90%	Top 10%
Stocks	$11101.84	$14457.24	$253294.60	$1347.287	$7295.84	$181340.80
Housing	$17023.78	$34898.17	$133766.50	$8087.49	$23415.30	$110630.50
Bonds	$345.82	$742.80	$6561.40	$43.60	$285.14	$2781.41

Table 2: Capital Gains from a 10% Asset Price Increase by Education and Income Group
NOTE: The table shows the numerical results from Fig. 9. All of the results are in 2019 US dollars.

Numerical results in Table 2 show that, averaged across all three asset classes, capital gains are 1.33 times larger for households in the top decile if they hold a degree, 1.62 times larger for households in the 50-90% range, and 3

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times larger for households at the lower end of the income distribution. It is important to highlight that such gains are computed in absolute value, i.e., not as a percentage increase in wealth.

4. Portfolio Effects of Expansionary Monetary Policy

This section investigates the movements of asset prices following an expansionary monetary policy shock. I first present the data and theoretical framework implemented, and then move on to show my findings.

4.1. Data; Macroeconomic Variables and Monetary Policy Shocks

To study how monetary policy shocks affect asset prices over a 48-month period, I use instrumental variable local projections (LP-IV) following Stock and Watson (2018) and Jordà (2005). For this purpose, I collect publicly available macroeconomic time series data as listed in Table 3.

Variable	Description	Source
Federal funds rate	Federal Funds Effective Rate	FRED
Industrial Production	Industrial production index	Mertens K. and M.O. Ravn (2013)
Unemployment rate	US unemployment rate	Mertens K. and M.O. Ravn (2013)
CPI	Consumer price index	Mertens K. and M.O. Ravn (2013)
Bond yield	Moody's BAA corporate bond yield (%)	FRED
Treasury yield	10 year treasury yield at constant maturity (%)	FRED
Stock prices	S&P composite price index	Robert J. Shiller's website
House prices	Case-Shiller house price index	Robert J. Shiller's website

Table 3: Macroeconomic Variables

NOTE: The table provides a description of the macroeconomic variables used in the local projections. It also specifies the source of each variable. All variables are at monthly frequency.

In order to identify the surprise component of variations in the federal funds rate, I use the monetary shock series developed by Romer and Romer (2004) and extended to December 2008. To generate their shock series, which is widely used in macroeconomic analysis, the authors infer the intended Federal Reserve's policy rate by examining minutes of the FOMC meetings. The intended policy rate is then regressed on the current federal funds rate and Greenbook forecast of output growth and inflation (as well as other controls); the residuals from this regression are used to measure the monetary policy shocks.

In the following analysis, I do not include the RR series as a direct measure of monetary policy shocks. This is because the series does not take into account the central bank's intended rate as inferred, for example, in speeches by FOMC members (see Stock and Watson (2018)). Therefore, while the RR variable remains correlated with the true unobserved shock, it does not capture it completely. Assuming the series is orthogonal to any other structural shock, it can be used as an instrumental variable for the actual surprise component of monetary policy. The following subsection includes greater details on the theoretical assumptions behind the LP-IV approach used in this article.

4.2. Methodology; Local Projections with IV Identification

The instrumental variable local projections method (LP-IV) allows to obtain impulse responses of macroeconomic variables over time following a monetary policy shock. Let r_t denote the federal funds rate at time t, and let y_{t+h} denote the outcome variable at time t + h. The model is implemented by estimating regression equation 4.2.1.

$$y_{t+h} = \alpha_h + \beta_h \hat{r}_t + \gamma_t^{'} X_t + u_{t+h} \quad \text{for} \quad h = 0, ..., H - 1. \tag{4.2.1}$$

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where H − 1 is the maximum horizon of the local projections (in this case 48 months). Note that $\hat{r}_t$ are predicted values of the federal funds rate from the first-stage regression:

$$r_t = a + \delta RRshock_t + \eta' X_t + \epsilon_{-r,t}. \tag{4.2.2}$$

The vector of controls X_t includes two lags of the outcome and shock variable.[2] It also includes contemporaneous values and two lags of the other endogenous variables and predetermined variables such as unemployment rate, industrial production index, CPI, and asset prices. As explained in Jordà et al. (2020), the inclusion of contemporaneous variables provides insurance against variation in the policy intervention known to agents at the time of the policy treatment.

The model relies on standard relevance and exogeneity assumptions for instrumental variable estimation. Let $\epsilon_{r,t}$ denote the actual monetary shock at time t; also let $\epsilon_{-r,t}$ denote any other structural shocks. Following Stock and Watson (2018), the assumptions can then be written as:

$$\begin{aligned}
&(i)\ \textit{Relevance:} \quad E[RRshock_t \cdot \epsilon_{r,t}] \neq 0. \\
&(ii)\ \textit{Contemporaneous exogeneity:} \quad E[RRshock_t \cdot \epsilon_{-r,t}] = 0. \\
&(iii)\ \textit{Lead-lag exogeneity:} \quad E[RRshock_t \cdot \epsilon_{t+j}] = 0 \quad \text{for} \quad j \neq 0.
\end{aligned}$$

Note that condition (iii), which is usually not included in standard IV models, arises because of the dynamics. In particular, the RR shock at time t must identify the shock $\epsilon_{r,t}$ alone. Hence, it must be uncorrelated with all other shocks at all leads and lags. It is worth noting that the instrument can be serially correlated yet still satisfy requirement (iii). To see why this is the case, suppose the following model holds:

$$RRshock_t = \theta \epsilon_{r,t} + \zeta_t. \tag{4.2.3}$$

where ζ_t is a serially correlated error term which is statistically independent of the sequence of serially uncorrelated structural shocks $\{\epsilon_t\}$: then, the instrument is auto-correlated but does satisfy the lead-lad exogeneity condition. Assuming the Greenbook forecast of future GDP growth and inflation contains all information used by the Federal Reserve to make its policy decisions, then if the Fed responds to a shock for reasons other than its effect on future output or inflation, this response (captured by the RR series) will satisfy the above conditions and can therefore be used as an instrument for monetary shocks .

Before turning to the empirical results, it is important to specify that the errors u_{t+h} are usually auto-correlated for h > 1. Therefore, I use heteroskedasticity- and autocorrelation-robust (HAC) standard errors in order to construct confidence intervals.

4.3. Results; Impulse Responses Following a Monetary Shock

Having obtained measures of asset price exposure by college education (see Section 3), I now study movements in stock and house prices over the 48 months following a 100bp expansionary monetary policy shock. Fig. 6 presents my estimates using the Romer and Romer shock series. More detailed results including confidence intervals are provided in Table 4

[2] The choice of 2 lags is optimal according to both Schwarz's Bayesian information criterion (SBIC), and the Hannan and Quinn information criterion (HQIC). Moreover, the final prediction error (FPE) and Akaike's information criterion (AIC) also recommend 2 lags for stock prices, whose impulse responses are the most sensible to the number of lags.

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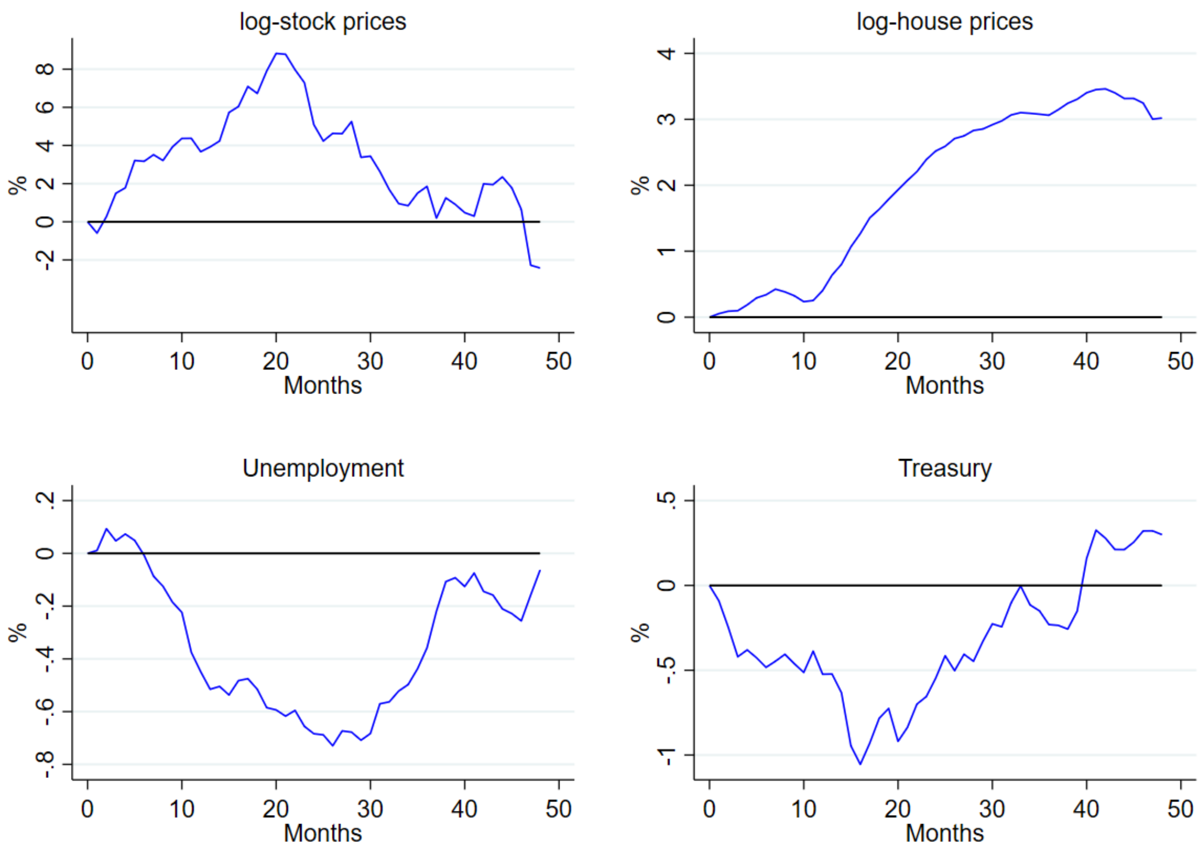

Figure 6

We can see that, consistently with findings by Bartscher et al. (2021), the increase in stock prices is the most prominent. My estimates show an increase in stock prices equal to 6.64% after only two years from the shock (such effect is statistically significant at the 5% level); it then reduces to 0.6% in the fourth year. It should be noted that Bartscher et al. (2021) find a roughly monotone increase in stock prices along a 5 year horizon. This is due to differences in the model specification (e.g. choice of lags) and the fact that they rely on a longer sample period. My results are in fact based on monthly data from March 1969 to December 2005 (Bartscher et al. use an extension of the Romer and Romer series and go up to 2015). Indeed, a recent paper by Paul (2020) finds that monetary policy today has more persistent effects on asset prices than before the global financial crisis.[3] As mentioned before, the last official extension of the series goes up to 2008. However, I decided not to include the years of the financial crisis in order to avoid potentially significant effects of confounding shocks to the macroeconomy. Appendix A.4 shows that reworking the empirics with the full sample (up to 2008) does not cause fundamental changes to the results. To provide further support for the empirical soundness of the estimates shown here, Appendix A.5 compares my results with those of Ramey's chapter for the Handbook of Macroeconomics (see Ramey (2016)). Ramey's results are obtained using the original Romer and Romer shock series (up to December 1996), and look remarkably similar to my own estimate.

[3] I decided not to use any extension of the Romer and Romer shocks. The series generally stops in 2008, given that this is when the zero lower bound on interest rates was reached. Following private communication with Professor Oliver Coibion, I preferred to limit my analysis to a slightly shorter time horizon rather than re-estimating the Romer and Romer shocks in an environment of bounded-below interest rates.

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Horizon	House prices %	Stock prices %	Unemployment rate pp	Treasury yield pp
Year 1	0.237	2.493	-0.091	-0.368
	[-0.236, 0.711]	[-1.871, 6.858]	[-0.293, 0.112]	[-0.711, 0.008]
Year 2	1.652**	6.64**	-0.563	-0.770
	[0.321, 2.983]	[0.418, 12.854]	[-0.969, -0.158]	[-1.428, -0.114]
Year 3	2.919***	2.920	-0.592	-0.264
	[1.158, 4.680]	[-3.135, 8.977]	[-0.976, -0.209]	[-0.809, 0.281]
Year 4	3.276***	0.596	-0.153	-0.145
	[1.266, 5.287]	[-5.240, 6.434]	[-0.546, 0.240]	[-0.537, 0.827]

Table 4: LP-IV Estimates for Response to 100bp Expansionary Monetary Policy Shock
* significant at 10%, ** significant at 5%, *** significant at 1%

NOTE: The rows for each shock series show the point estimates of the response after 1 to 4 years. Square brackets below the point estimates at each horizon show the 95-percent confidence intervals.

House prices are initially sticky, which is consistent with textbook macroeconomics. They then start increasing following a bell-shaped behaviour (this is more evident when the horizon is extended to 60 months, and is similar to point estimates in Bartscher et al. (2021)). After 4 years from the shock, the increase in house prices is around 3.3%, and is strongly significant. In appendix A.6 I provide impulse responses for all the variables included in my model.

Note that the relation between bond yields and their prices could be added to the capital gains which I present in the next section. However, given that exposure to bond prices shown in Fig. 5 pales compared to capital gains from stock- and house-market booms, this paper neglects their portfolio effects. Including such bond effects is not likely to lead to significantly different results. If anything, given that bonds make up a higher percentage of wealth for college-educated households, an increase in their prices would add to the wealth inequality caused by the monetary shock.

5. Combining Macro and Micro Data: The Distributional Effect of MP Shocks

Given my estimates of asset price effects of monetary easing, it remains to combine such results with evidence from the survey data shown in Section 3.2. The objective is to compute capital gains by college education and income groups following a 100bp expansionary Romer and Romer shock. I first do so in absolute levels (i.e., showing gains in thousands of dollars), and then as a percentage increase in wealth.

5.1. Absolute Capital Gains from Monetary Shock

In order to compute capital gains, I multiply the yearly averages in asset price changes shown in Table 4 with the average holdings of housing and stocks found in 2019 in the survey data. In particular, assume the monetary shock occurs at time t. Following Kuhn et al. (2018), let $A^i_{j,t}$ denote holdings of asset j by household i in period t; in this case, j = {housing, stocks}. Let also Π^i_{t+h} denote capital gains of the individual at time t + h, where h (= 0, 1, 2, 3, 4) indicates the number of years after the shock occurred. Finally, I define the price index for asset j a time t as $P^i_{j,t}$. We can then express capital gains every year following the shock as:

$$\Pi^i_{t+h} = \left(\frac{P_{housing,t+h}}{P_{housing,t}} - 1\right) \cdot A^i_{housing,t} + \left(\frac{P_{stocks,t+h}}{P_{stocks,t}} - 1\right) \cdot A^i_{stocks,t} \qquad (5.1.1)$$

In this case, gains are averaged across households by college group. Moreover, as in the earlier discussion, I preserve the distinction by income group so as to highlight potential differences in capital gains along the income distribution. My results are shown in Fig. 7. Capital gains are larger for households with a college degree every year following the shock. Importantly, this is true across all income groups.

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Figure 7

The largest effect in the first two years from the shock comes from significant changes in equity prices. Because the increase in house prices is more persistent, the 'housing effect' dominates the 'equity effect' in the third and fourth year. Consistently, Fig. 7 shows that households with a college degree benefit particularly in the second year following the shock, with capital gains approaching $10,000, $15,000, and roughly $180,000 respectively for households in the bottom 50%, between 50 and 90%, and top 10% of the income distribution. On the other hand, households without a college degree and in the bottom 90% of the distribution hold a larger share of their wealth in housing, which is reflected in capital gains being maximal in the third year. Nevertheless, the richest amongst the non-college educated also save the majority of their wealth in equity, which is reflected in capital gains being highest in the second year following the shock. In general, gains to non-college households peak at roughly $3,000, $8,000, and $140,000 along the income distribution.

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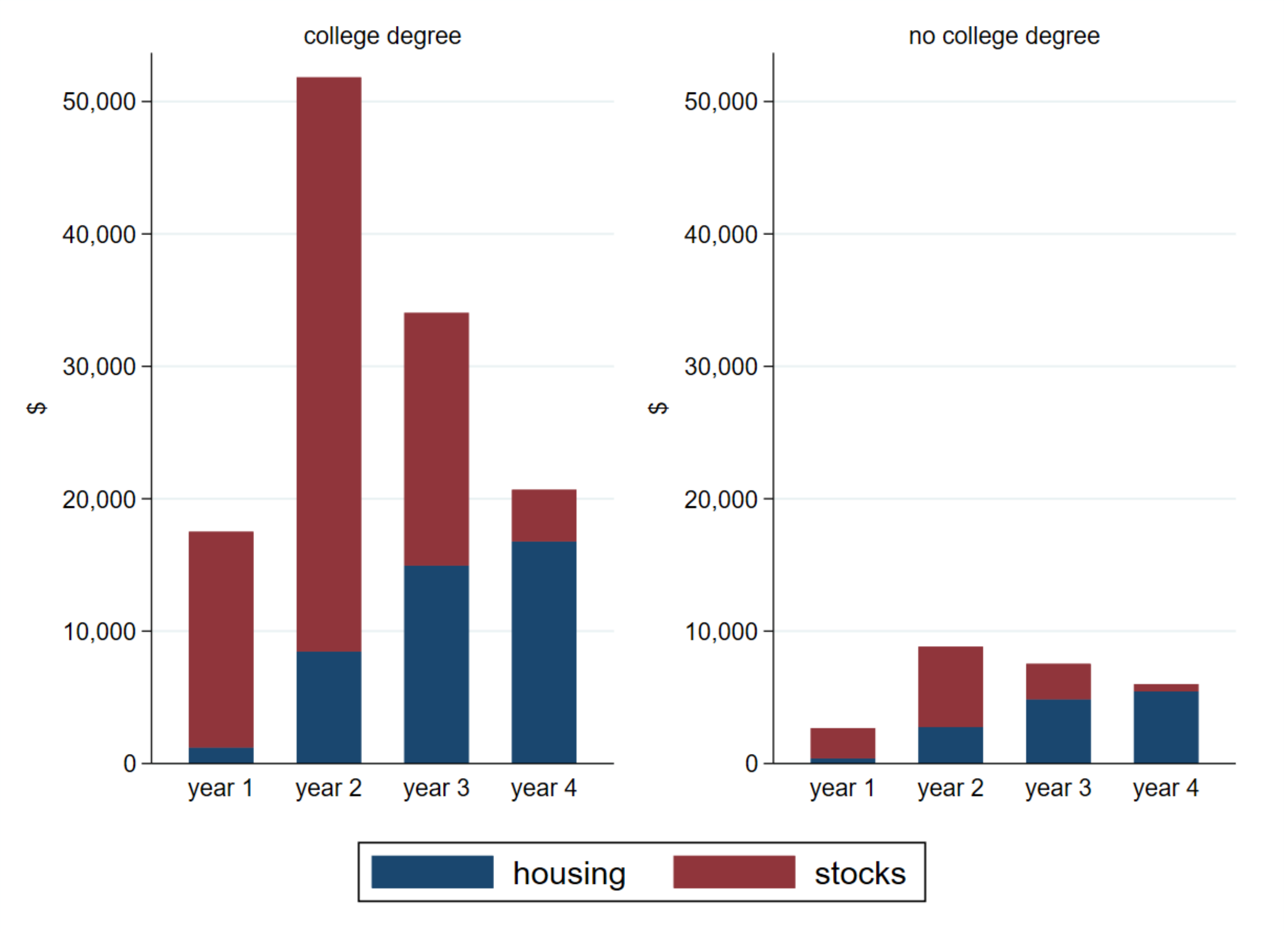

Figure 8

It follows that the college-wealth gap increases substantially following an expansionary monetary shock. It is very important to highlight that the increase in wealth inequality holds for all three income groups. Fig. 8 shows capital gains without sorting by income group. As mentioned before, results are re-weighted to account for over-sampling of wealthy households and should therefore be interpreted as gains to the average household with and without a college degree in the United States. The magnitude of the distributional effect is striking. At the peak, households with a college degree gain over $50,000, compared to less than one fifth for households without a college degree.

Before drawing conclusions, in the next section I also investigate whether results look substantially different if gains are computed as a percentage change in total wealth rather than in dollars.

5.2. Capital Gains as a Percentage Increase in Wealth

The claim that wealth inequality has increased following monetary expansion depends on how inequality itself is measured. So far, I have been thinking about wealth inequality between college and non-college households as simply the gap (in dollars) between the average wealth of the two groups. An expansionary monetary shock widens such a gap since households with a college degree reap greater capital gains from the resulting house- and stock-market expansions.

However, since non-college households hold a larger share of their wealth in housing, we might expect capital gains to be larger than for college households after the second year from the shock (since house prices continue to increase while stock prices increase only temporarily). This is at odds with results shown in Fig. 7. The reason is that while college-educated families save a lower share of their capital in housing, such share still constitutes a higher dollar figure than for non-college households. Consequently, absolute capital gains remain larger for households with a college degree.

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It is interesting to check whether wealth gains are more equally distributed if measured as a percentage increase in existing wealth. In order to do so, I simply divide the capital gains shown in Fig. 7 by pre-shock wealth.

More formally, let W_t^i denote household wealth at time t (i.e., at the time of the shock). The percentage change in wealth at time t + h is given by:

$$\frac{\Pi_{t+h}^i}{W_t^i} = \left(\frac{P_{housing,t+h}}{P_{housing,t}} - 1\right) \cdot \frac{A_{housing,t}^i}{W_t^i} + \left(\frac{P_{stocks,t+h}}{P_{stocks,t}} - 1\right) \cdot \frac{A_{stocks,t}^i}{W_t^i}$$

$$\rightarrow q_{t+h}^i = \left(\frac{P_{housing,t+h}}{P_{housing,t}} - 1\right) \cdot \alpha_{housing,t}^i + \left(\frac{P_{stocks,t+h}}{P_{stocks,t}} - 1\right) \cdot \alpha_{stocks,t}^i \qquad (5.2.1)$$

Where q_{t+h}^i denotes the growth rate of household wealth from capital gains and $\alpha_{j,t}^i$denotes the portfolio share of asset j. As in the previous subsection, results are shown for the average household by college education and income group.

Fig. 9 shows percent changes in wealth over time. As expected, the figure tells a very different story from the findings shown in Section 5.1. Indeed, monetary easing seems more or less neutral, with college-households gaining slightly more in years immediately following the shock – due to the rapid uptake in stock prices – and non-college households experiencing larger percentage gains in the last two years thanks to the persistent increase in house prices.

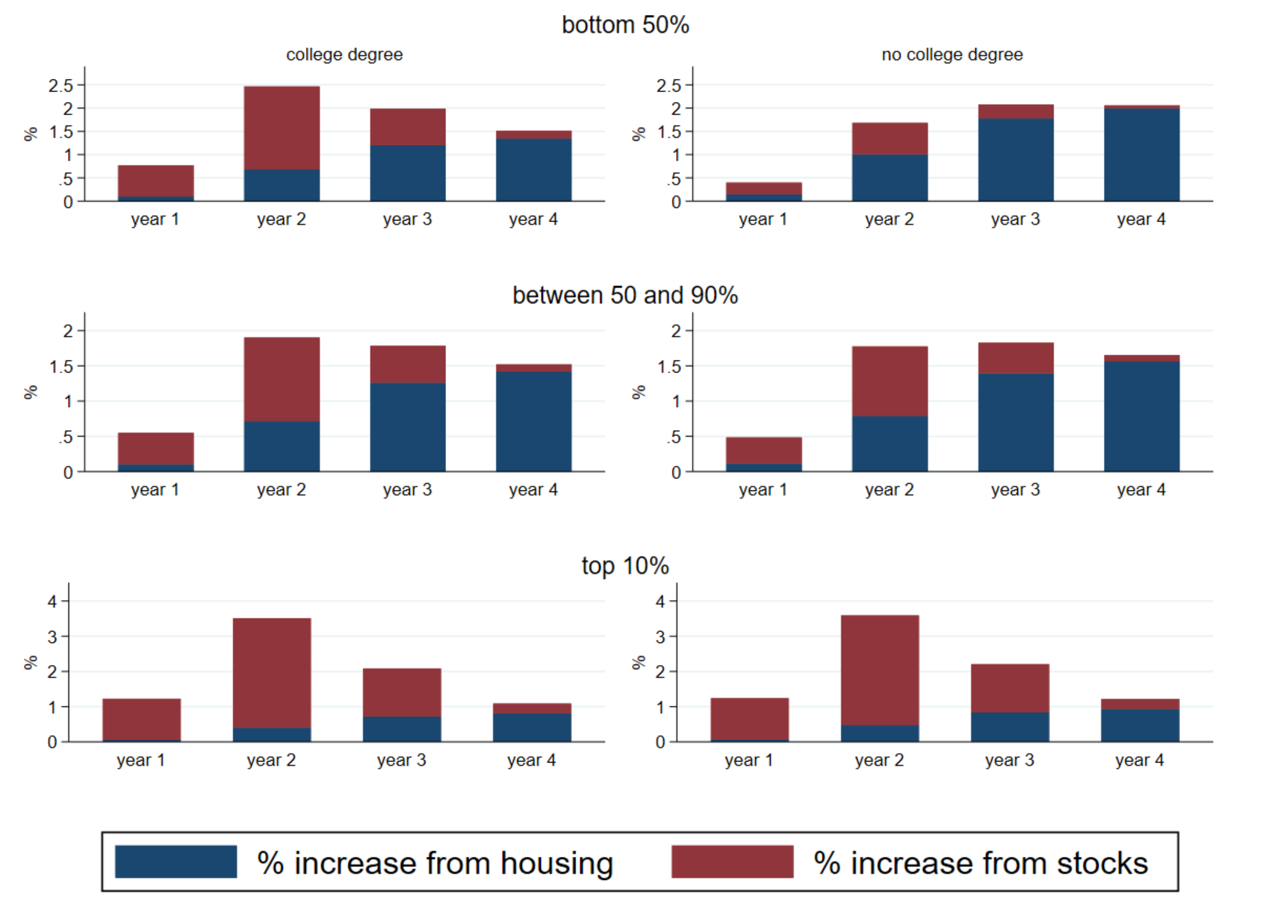

Figure 9

Moreover, households in the bottom 50% of the income distribution attain a larger percent increase in wealth than households in the 50-90% group. This is true for both college and non-college households. Nevertheless, households in the top 10% continue to take up the largest percentage gain in the short run. Note that this is consistent with simulations by Albert and Gòmez-Fernàndez (2018), whom I mentioned earlier in Section 2.1.

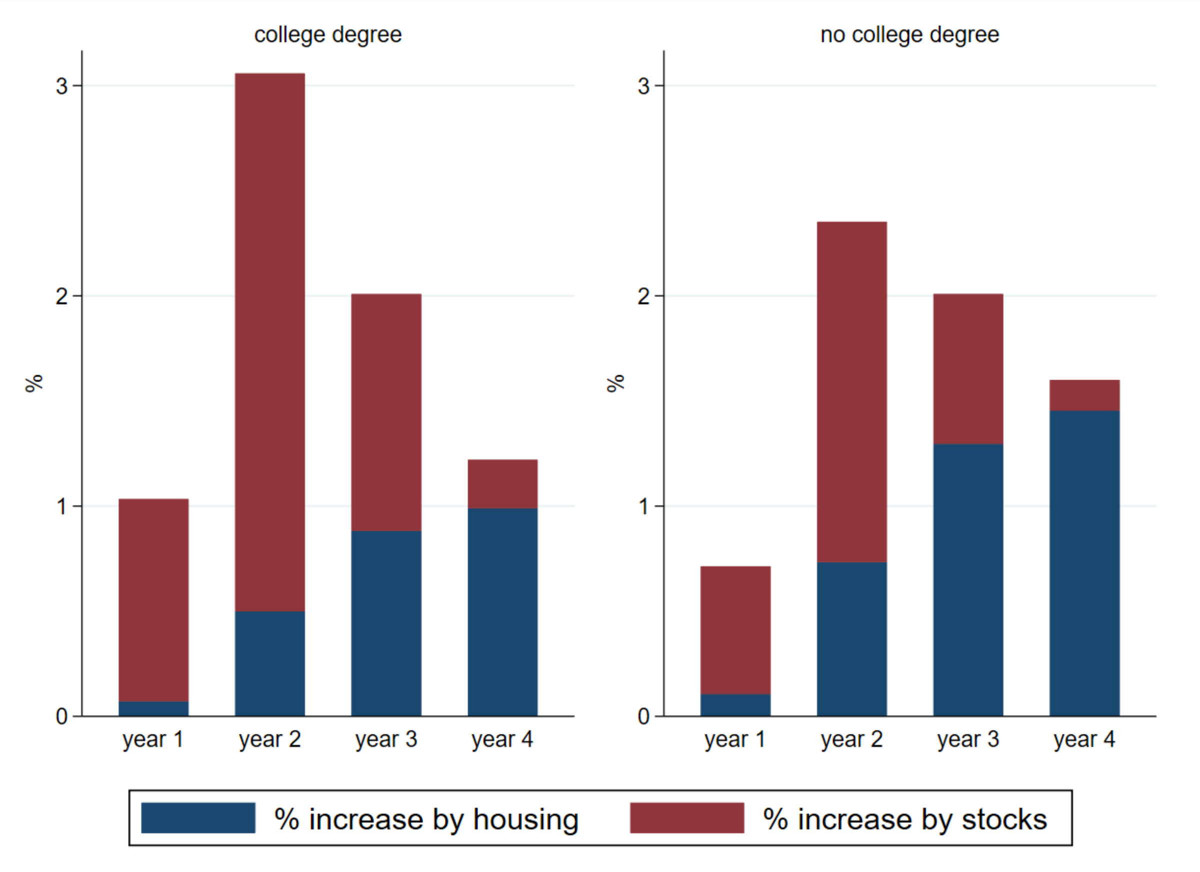

Figure 10

Fig. 10 shows the same result for the average household in the two educational groups. Despite the results in this subsection, it should be noted that, given how unequal the initial distribution of wealth between college and non-college households is (see Fig. 5), absolute capital gains are probably more relevant to inequality than per cent ones.

6. Conclusion

In this paper, I start by using survey data in order to highlight how households with and without a college degree in the United States diversify their portfolio across a range of asset classes. The key result from this analysis is that college-educated households are significantly more exposed to absolute capital gains following stock- and house-market booms compared to less educated families. I move on to analysing the movements in asset prices following a 100bp expansionary monetary policy shock. For this purpose, I compute local projections of asset prices using the Romer and Romer (2004) shock series as an instrumental variable for exogenous shocks to the federal funds rate. To complete the empirical analysis, I combine the point estimates from the LP-IV model with evidence from the survey data; this allows me to measure capital gains over time following a monetary easing shock. My results show that capital gains are unevenly distributed, as households with a college degree benefit disproportionately from the shock. However, this appears much less evident when gains are computed as percentage changes in existing wealth.

In light of the aforementioned results, I argue that monetary policy alone lacks the tools to stimulate economic activity without exacerbating wealth inequalities by college education. When these findings (specific to one dimension of inequality) are coupled with the rapidly growing literature highlighting potential adverse distributional consequences of monetary policy, a more general conclusion may be drawn, i.e., that monetary policy is limited in its ability to respond to economic shocks without creating winners and losers.

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A. Appendix

A.1. College wealth premium over time: numerical results

Year	College wealth (1971=1)	Non-College wealth (1971=1)	%Δ
1956	.6267884	.549124	14.14333
1959	.4853575	.5842781	-16.9304
1962	.6124887	.6570373	-6.78022
1965	.8567906	.714197	19.96559
1968	.8463688	.8333674	1.560102
1971	1	1	0
1977	.6813924	.8034222	-15.18876
1983	1.822716	1.330085	37.03754
1989	2.423776	1.520171	59.44103
1992	1.967857	1.309597	50.26429
1995	2.18729	1.431314	52.81685
1998	2.868962	1.599363	79.38152
2001	3.895438	1.758342	121.5404
2004	3.890948	1.874464	107.5765
2007	4.604863	2.069776	122.4813
2010	3.905869	1.607654	142.9545
2013	3.794202	1.575135	140.8811
2016	4.750671	1.787381	165.7895
2019	4.50456	1.919004	134.7342

Table 5: Wealth Comparison of Households with College versus Without

NOTE: Wealth is normalized to equal 1 in 1971. %Δ gives the percentage difference between the two educational groups.

A.2. The effect of college education on wealth: regression output

As the table shows, the effect of obtaining a college degree on wealth is strongly significant from 1998 onwards and follows a (roughly) monotone increase over time.

Year	College effect in 10,000 USD ($\hat{\beta}_1 + \hat{\beta}_{2,t}$)	95% Confidence band
1956	-.5002747	(-57.89606; 56.89551)
1959	1.802269	(-30.05409; 33.65863)
1962	13.12164	(-15.53878; 41.78207)
1965	5.796158	(-21.69874; 33.29107)
1968	15.72237	(-9.608994; 41.05374)
1971	2.381531	(-21.88172; 26.64478)
1977	3.057629	(-16.15663; 22.27189)
1983	10.94407	(-5.954415; 27.84255)
1989	10.42212	(-5.596049; 26.44029)
1992	8.784672	(-6.137711; 23.70706)
1995	13.82434*	(-1.310729; 28.95942)
1998	24.69012***	(10.15027; 39.22997)
2001	39.46104***	(25.55952; 53.36258)
2004	36.27906***	(22.90413; 49.65399)
2007	51.52709***	(38.20794; 64.84625)
2010	40.76389***	(27.7395; 53.78827)
2013	39.77309***	(27.13498; 52.41119)
2016	54.60931***	(42.33622; 66.88242)
2019	61.0411***	(49.08522; 72.99699)
N	90,798	
R^2	0.258	

Table 6: Numerical Results from Regression Equation 3.2.1
* significant at 10%, ** significant at 5%, *** significant at 1%

NOTE: Confidence interval on the sum of coefficients is computed using the STATA "lincom" command

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A.3. Portfolio shares by asset class: supplementary table

(a) College households

Year	Bonds	Housing	Equity	Liquid assets	Other financial assets	Other non-financial assets
1956	5.937954	29.34737	57.09644	7.730965	-	2.653324
1959	6.131933	25.53371	61.848	7.174732	-	1.845932
1962	6.772285	25.54286	59.27597	8.175241	-	1.514829
1965	3.402571	25.70001	62.98799	7.709291	-	1.238199
1968	1.288316	24.49851	63.55335	6.052444	-	1.495297
1971	2.524129	32.071	53.67453	8.792433	-	1.672722
1977	2.7025	38.42984	47.85933	5.473329	-	2.525058
1983	4.778366	36.5979	33.77458	9.082629	6.297286	3.282861
1989	4.237055	39.51069	28.72168	7.498652	11.79768	4.394984
1992	4.298407	39.3724	28.72742	6.971585	12.91125	4.195171
1995	3.935005	33.85205	31.89407	7.303695	15.53601	4.478155
1998	2.403647	30.32084	35.99777	5.913455	16.22614	3.611598
2001	3.038571	30.9603	35.60582	5.388527	16.0471	3.24869
2004	2.763275	36.93427	33.44001	5.301967	14.53162	3.251069
2007	2.017516	35.61112	36.07779	5.002929	15.03202	2.588035
2010	2.3664	34.53954	32.17069	6.267098	17.81671	2.770983
2013	1.648084	32.12243	33.55599	6.300946	19.0603	2.797332
2016	1.579925	29.25165	40.01778	5.634732	16.95485	2.266642
2019	1.116331	30.22495	38.55726	5.517036	17.53688	2.337742

(b) Non-college households

Year	Bonds	Housing	Equity	Liquid assets	Other financial assets	Other non-financial assets
1956	4.424397	32.55101	54.96263	6.94904	-	3.091208
1959	4.360598	34.00901	53.33591	6.956555	-	3.006335
1962	3.926248	39.59349	46.61382	7.272497	-	2.565958
1965	2.635796	39.87172	48.37562	6.5934	-	2.998896
1968	2.090014	39.24018	46.64675	8.127467	-	3.144223
1971	2.898336	41.6888	42.74463	8.570876	-	3.145674
1977	2.68506	49.23365	33.11551	9.45458	-	4.245821
1983	2.518537	49.24622	23.347	9.482258	6.358334	5.062443
1989	3.40831	48.76086	21.46533	10.12076	8.762269	6.275779
1992	2.270061	49.33178	21.94078	9.251513	9.598536	5.734611
1995	2.623559	43.66417	23.69422	7.086314	13.1514	7.297844
1998	2.158602	44.24731	24.92357	6.927844	12.55953	6.241867
2001	1.554421	44.23549	22.28495	7.664836	14.22123	6.17267
2004	1.378335	51.23885	18.32539	7.296607	11.50975	6.000806
2007	1.167179	50.95959	21.82093	5.285811	12.06948	5.37459
2010	.8399956	48.82278	20.3988	7.052958	13.49296	6.306177
2013	1.264858	45.01187	22.50711	6.117165	15.02654	6.273127
2016	.9293516	44.40733	22.46158	5.590039	16.23932	6.070956
2019	.5716136	44.39538	24.39665	6.169841	14.52568	5.785607

Table 7: Portfolio Shares by Asset Class in the 2019 SCF. Numerical Results

NOTE: The table shows the portfolio shares of other non-financial assets, housing, equity, liquid assets, and bonds, as well as other financial assets for college and non-college households over time

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A.4. Impulse responses using the full RR shock

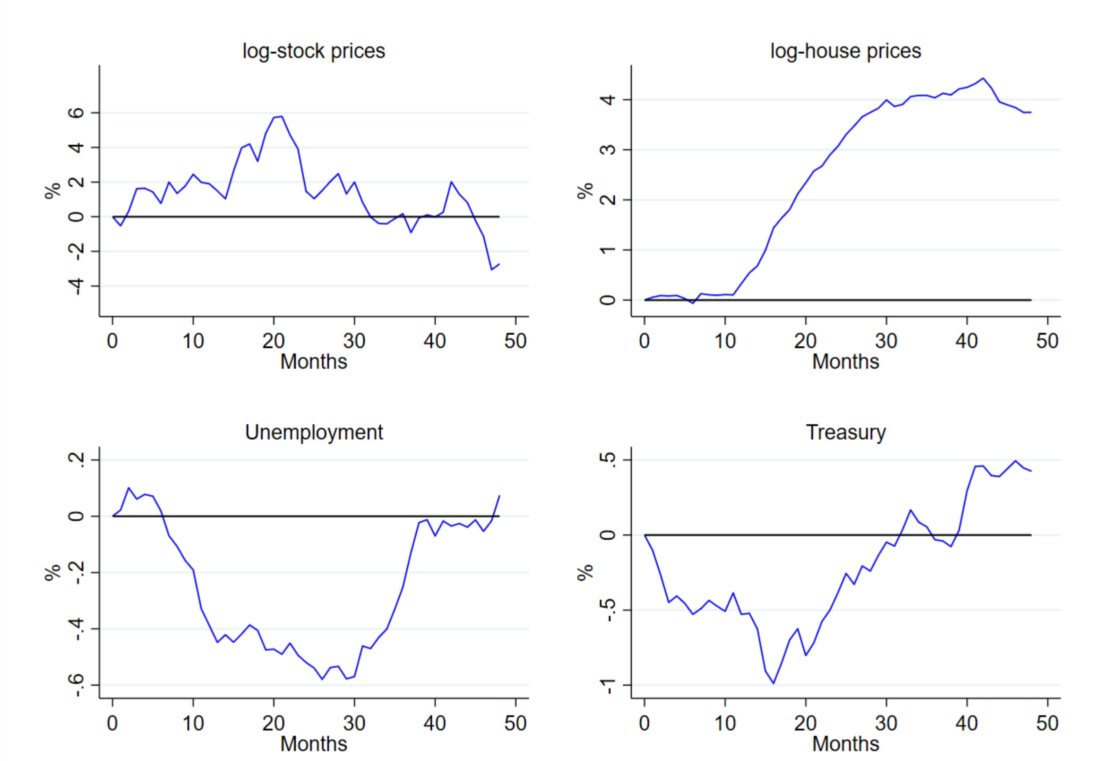

Figure 11

The empirical analysis of this article has been carried out by dropping observations in the years 2006-2008. This was in order to avoid the effect of the global financial crisis. In this section, I re-estimate the impulse responses using the full sample of the Romer and Romer shocks – i.e., up to December 2008.

As we can see, the overall behaviour of each variable remains unchanged. The increase in stock prices remains the most prominent, and the peak is again reached after 20 months. The main difference is that the maximum increase is now roughly 6% compared to just above 8% by truncating the sample. As for house prices, the overall picture is again almost unchanged. Prices are still initially sticky for the first 10 months, and then start increasing in a concave fashion. The peak is slightly above the one found by truncating the sample, but it still occurs after roughly 40 months from the shock. Finally, the responses of unemployment rate and treasury yield are indeed basically unchanged. Overall, this shows that including the full sample of the RR shocks would not have led to significantly different results.

A.5. Comparison with Ramey's chapter on macroeconomic shocks

As mentioned in Section 4, here I compare results from the LP-IV model implemented in this study with impulse responses by Ramey (2016). In the figure below, panel (a) shows Ramey's estimated impulse responses of the federal funds rate, CPI, industrial production index, and unemployment rate following a 100bp contractionary Romer and Romer shock. The lower panel shows my projections following the same shock. Ramey uses the original RR series from 1969m3 to 1996m12, while I use the updated series up to December 2005.

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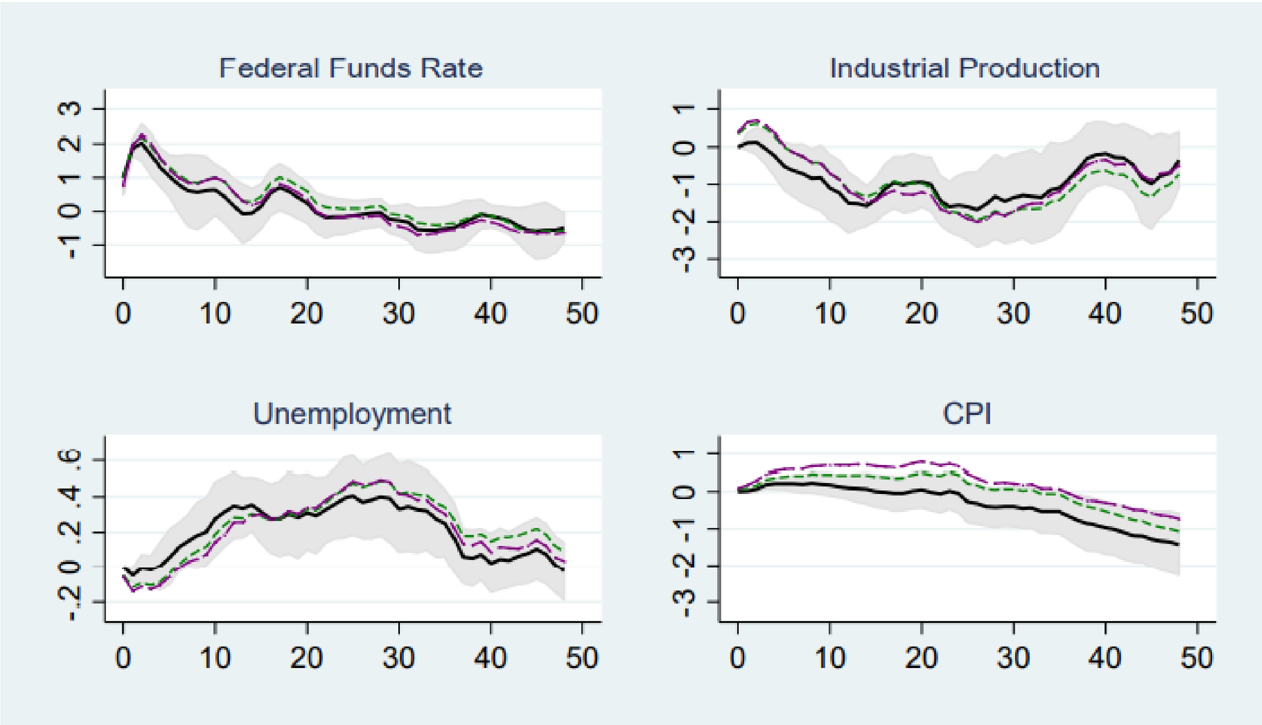

Figure 12(A)

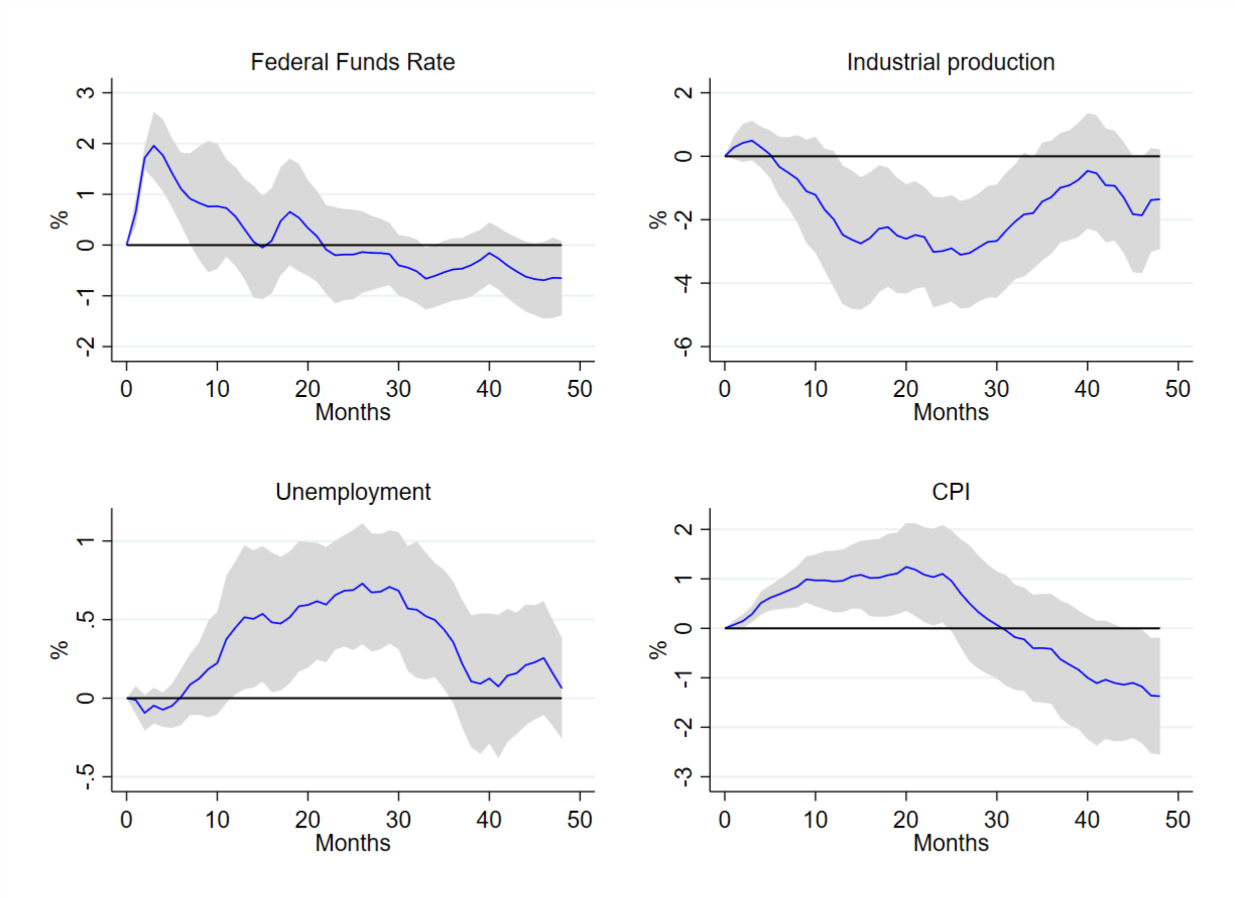

Figure 12(B)

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A.6. Impulse responses: complete results

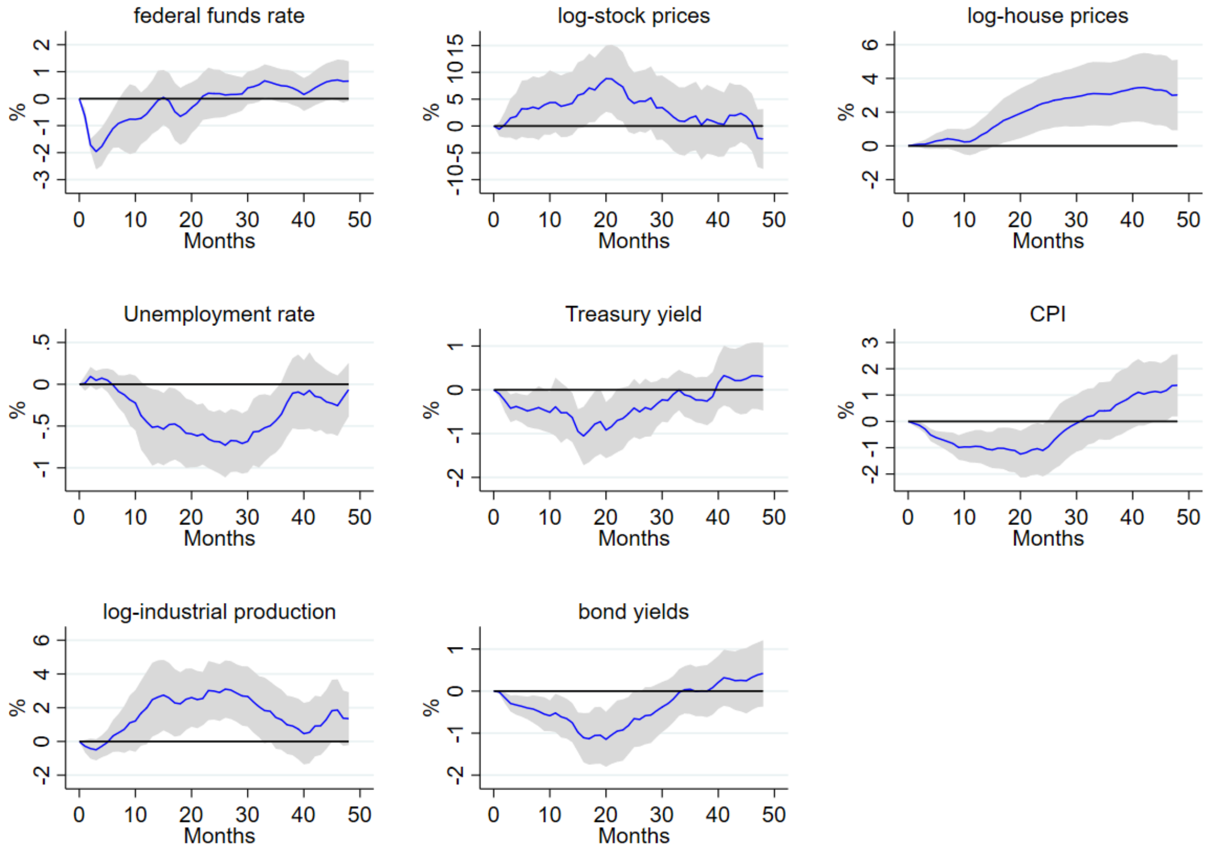

Figure 13

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